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Analysis of Productivity Improvement in the Construction Sector

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ABSTRACT

Productivity improvement in the construction sector is a critical factor in ensuring project success, particularly in terms of time efficiency, cost control, and optimal resource utilization. This study aims to analyze the key factors influencing construction productivity and to develop an effective productivity improvement model based on empirical data. A quantitative research approach was employed using Structural Equation Modeling (SEM) to examine the relationships between inventory management, information technology utilization, employee training and development, analytical data integration, and competent human resources on construction productivity. Data were collected from construction workers and employees in West Sumatra through questionnaires, interviews, observations, and focus group discussions. The reliability test results indicate a high level of internal consistency, with Cronbach's Alpha values exceeding 0.8. The SEM analysis demonstrates that inventory management, information technology, training and development, data integration, and competent human resources have a significant and positive influence on construction productivity, explaining 87.5% of the variance in productivity performance. The findings suggest that an integrated management approach focusing on technological support and human resource competence is essential for improving productivity in the construction sector.

Keywords: *construction productivity, information technology, inventory management, human resources, structural equation modeling.*

1. INTRODUCTION

Productivity in the construction industry plays a crucial role in determining overall project performance, particularly in terms of cost efficiency, timely completion, and quality achievement. Construction projects are inherently complex, involving dynamic site conditions, intensive labor utilization, extensive material handling, and coordination among multiple stakeholders. These characteristics make construction productivity highly vulnerable to managerial inefficiencies and operational disruptions (Hwang & Ng, 2013; Nasirzadeh et al., 2014).

In many developing countries, including Indonesia, low construction productivity remains a persistent challenge that negatively affects infrastructure development and economic growth. Previous studies have reported that productivity losses in construction projects are often caused by poor planning, inadequate material management, limited technological adoption, and insufficient workforce competence (Doloi et al., 2012; Durdyev & Ismail, 2016). Such conditions highlight the importance of adopting integrated management approaches to address productivity issues comprehensively. Inventory management is widely recognized as a critical factor influencing construction productivity. Ineffective inventory control can lead to material shortages, excessive stock, increased waste, and project delays, all of which reduce productivity performance (Vrijhoef & Koskela, 2000). Conversely, effective inventory management supported by accurate data and systematic control mechanisms enables smoother workflow and optimal resource utilization on construction sites (Kasim et al., 2018).

Alongside inventory management, the utilization of information technology has become increasingly important in modern construction management. Information technology facilitates real-time data exchange, improves coordination among project participants, and enhances decision-making accuracy (Love et al., 2014). Digital tools such as project management software, data analytics platforms, and integrated information systems have been shown to significantly improve construction productivity when properly implemented (Oesterreich & Teuteberg, 2016). However, technological investment alone does not guarantee productivity improvement without adequate human resource capability.

Employee training and development play a pivotal role in enabling effective technology adoption and improving overall work performance. Well-trained employees are more capable of adapting to new systems, complying with standardized procedures, and responding to changing project conditions (Sweis et al., 2016). Training programs also contribute to reducing errors, enhancing safety awareness, and increasing labor efficiency, which collectively support productivity improvement (Loosemore et al., 2018).

Furthermore, the integration of analytical data into construction management processes allows organizations to monitor performance indicators, predict potential delays, and optimize resource allocation. Data-driven decision-making has been identified as a key enabler of productivity improvement in construction projects, particularly when supported by competent human resources capable of interpreting and utilizing analytical information effectively (Whyte et al., 2016). Human resource competence therefore acts as a mediating factor that links organizational systems and technological tools to actual productivity outcomes.

Despite the growing body of literature on construction productivity, many previous studies have examined these influencing factors in isolation, using descriptive or partial analytical approaches. Limited research has empirically investigated the combined effects of inventory management, information technology utilization, employee training and development, analytical data integration, and competent human resources within a single comprehensive framework, particularly in the context of Indonesian construction projects (Doloi et al., 2012; Durdyev & Ismail, 2016).

To address this research gap, this study employs Structural Equation Modeling (SEM) to analyze the interrelationships among key determinants of construction productivity in West Sumatra, Indonesia. SEM is a robust multivariate analysis technique that enables simultaneous examination of complex causal relationships between latent variables (Hair et al., 2019). By applying SEM, this study aims to provide a deeper understanding of how managerial, technological, and human resource factors interact to influence productivity performance in the construction sector.

Therefore, the objectives of this study are:

1) to identify key factors influencing construction productivity in West Sumatra;
2) to analyze the direct and indirect relationships among inventory management, information technology utilization, employee training and development, analytical data integration, competent human resources, and construction productivity; and
3) to develop an integrated productivity improvement model based on empirical evidence.

The findings of this study are expected to contribute theoretically by enriching the construction management literature with an integrated SEM-based productivity model. Practically, the results provide insights for construction companies and policymakers in formulating effective productivity improvement strategies through technology adoption, workforce development, and integrated management systems.

2. LITERATURE REVIEW

2.1 Construction Productivity

Construction productivity is generally defined as the ratio between output produced and input resources utilized, such as labor, materials, equipment, and capital. High productivity indicates efficient resource utilization, whereas low productivity reflects operational inefficiencies and management shortcomings (Jarkas & Bitar, 2012). In the construction sector, productivity is influenced by a wide range of interrelated factors due to the project-based and labor-intensive nature of construction activities. Previous studies have emphasized that construction productivity is not solely determined by labor performance but also by managerial practices, technological support, and organizational capability. Doloi et al. (2012) found that productivity improvement requires an integrated approach that combines planning efficiency, resource coordination, and workforce competence. Similarly, Nasirzadeh et al. (2014) highlighted that productivity fluctuations are strongly affected by dynamic interactions among labor, materials, and information flow on construction sites.

2.2 Inventory Management and Construction Productivity

Inventory management plays a critical role in ensuring the smooth execution of construction activities. Poor inventory control can result in material shortages, work interruptions, excess inventory, and increased waste, all of which negatively affect productivity (Vrijhoef & Koskela, 2000). Effective inventory management ensures that materials are available in the right quantity, at the right time, and at the right location, thereby supporting uninterrupted workflow and optimal labor utilization. Kasim et al. (2018) demonstrated that construction projects with systematic inventory planning and real-time material tracking achieve higher productivity levels compared to projects relying on conventional material management practices. Furthermore, integrated inventory systems supported by digital tools enable better coordination between suppliers, contractors, and on-site teams, reducing delays and uncertainty (Love et al., 2014). These findings suggest that inventory management is a fundamental determinant of construction productivity.

2.3 Information Technology Utilization in Construction

The utilization of information technology (IT) has become increasingly important in modern construction management. IT applications such as project management software, enterprise resource planning (ERP), and data analytics platforms facilitate real-time communication, improve data accuracy, and enhance decision-making processes (Oesterreich & Teuteberg, 2016). Through improved information flow, IT reduces coordination errors and supports efficient resource allocation. Several empirical studies have confirmed the positive relationship between IT utilization and construction productivity. Love et al. (2014) reported that digital information systems significantly reduce rework and improve schedule adherence. However, the effectiveness of IT adoption largely depends on organizational readiness and the capability of human resources to operate and interpret digital systems (Whyte et al., 2016). Without adequate skills and training, technological investments may fail to deliver expected productivity gains.

2.4 Employee Training and Development

Employee training and development are essential for improving construction productivity by enhancing workers' technical skills, adaptability, and safety awareness. Well-trained employees are better equipped to follow standardized procedures, utilize technological tools, and respond to changing project conditions (Sweis et al., 2016). Training programs also contribute to reducing errors, minimizing accidents, and increasing labor efficiency (Loosemore et al., 2018). In addition, continuous training supports organizational learning and knowledge transfer, which are crucial for sustaining productivity improvement over time. Durdyev and Ismail (2016) emphasized that construction firms investing in systematic training programs tend to achieve higher productivity and better project performance. These findings underline the strategic importance of human capital development in construction management.

2.5 Analytical Data Integration

Analytical data integration refers to the systematic collection, processing, and utilization of project-related data to support decision-making. Data-driven construction management enables project managers to monitor performance indicators, identify potential risks, and optimize resource allocation (Whyte et al., 2016). The integration of analytical data enhances transparency and reduces uncertainty in project execution. Recent studies have shown that construction projects utilizing data analytics and integrated information systems experience improved productivity and reduced variability in performance outcomes (Oesterreich & Teuteberg, 2016). However, the benefits of data integration depend on the availability of competent personnel capable of interpreting analytical results and translating them into effective management actions (Hair et al., 2019).

2.6 Human Resource Competence

Human resource competence encompasses technical skills, experience, problem-solving ability, and adaptability to new technologies. Competent human resources are a key enabler of productivity improvement, as they mediate the relationship between organizational systems and operational performance (Sweis et al., 2016). In construction projects, skilled workers and managers contribute to efficient coordination, quality control, and timely decision-making. Empirical evidence suggests that human resource competence has both direct and indirect effects on construction productivity. Doloi et al. (2012) found that workforce competence strengthens the impact of managerial and technological factors on productivity outcomes. This indicates that human resources play a central role in transforming organizational inputs into tangible productivity gains.

2.7 Research Gap and Conceptual Framework

Although previous studies have extensively examined factors influencing construction productivity, most research has focused on individual determinants in isolation. Limited studies have empirically investigated the combined effects of inventory management, information technology utilization, employee training and development, analytical data integration, and human resource competence within a single comprehensive model, particularly using Structural Equation Modeling (SEM) in the Indonesian construction context. Therefore, this study proposes an integrated conceptual framework that examines both direct and indirect relationships among these variables using SEM. By addressing this research gap, the study aims to provide a more holistic understanding of construction productivity determinants and offer evidence-based recommendations for productivity improvement.

3. METHODOLOGY

3.1 Research Design

This study adopts a quantitative research design with an explanatory approach to examine the relationships among factors influencing construction productivity. The research employs Structural Equation Modeling (SEM) as the main analytical technique to analyze both direct and indirect effects among latent variables. SEM is particularly suitable for this study because it enables simultaneous testing of multiple relationships and accommodates complex interactions among organizational, technological, and human resource factors (Hair et al., 2019).

3.2 Research Location and Population

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The study was conducted in West Sumatra, Indonesia, focusing on construction companies and project sites operating in the region. The research population consists of construction workers, site engineers, supervisors, and managerial staff involved in ongoing construction projects. This population was selected due to their direct involvement in project execution and productivity-related decision-making processes.

3.3 Sampling Technique and Sample Size

A purposive sampling technique was employed to select respondents who met specific criteria:
(1) actively involved in construction projects in West Sumatra,
(2) having at least one year of work experience in the construction sector, and
(3) possessing sufficient knowledge of project operations and management practices.
A total of 75 respondents participated in the study. This sample size satisfies the minimum requirements for SEM analysis, which recommend at least 5–10 observations per estimated parameter to ensure reliable model estimation (Hair et al., 2019).

3.4 Data Collection Methods

Data were collected using a structured questionnaire as the primary instrument. The questionnaire was developed based on established literature and adapted to the construction context of Indonesia. In addition to questionnaires, interviews, field observations, and focus group discussions (FGDs) were conducted to enrich data interpretation and validate survey findings. The questionnaire was distributed both in printed form and electronically to facilitate broader participation. Respondents were assured of confidentiality to encourage honest and accurate responses.

3.5 Measurement of Variables

The study examines six latent variables:

1) **Inventory Management (IM)**
   Measured using indicators related to material availability, inventory control, stock accuracy, and coordination with suppliers (Vrijhoef & Koskela, 2000).
2) **Information Technology Utilization (IT)**
   Assessed through indicators capturing the use of project management software, digital communication systems, and data management tools (Oesterreich & Teuteberg, 2016).
3) **Employee Training and Development (TD)**
   Measured by indicators related to training frequency, skill development programs, and learning opportunities (Sweis et al., 2016).
4) **Analytical Data Integration (ADI)**
   Evaluated through indicators concerning data collection, data processing, performance monitoring, and data-driven decision-making (Whyte et al., 2016).
5) **Human Resource Competence (HRC)**
   Measured using indicators reflecting technical skills, experience, problem-solving ability, and adaptability to technological changes (Doloi et al., 2012).
6) **Construction Productivity (CP)**
   Measured through indicators related to work efficiency, time performance, cost effectiveness, and quality achievement (Jarkas & Bitar, 2012).

All indicators were measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

3.6 Validity and Reliability Testing

Prior to SEM analysis, the measurement model was evaluated for validity and reliability. Construct validity was assessed using Confirmatory Factor Analysis (CFA) by examining factor loadings, with values $\geqslant$ 0.50 considered acceptable. Reliability was evaluated using Cronbach's Alpha and Composite Reliability (CR), with threshold values $\geqslant$

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0.70. Convergent validity was confirmed through Average Variance Extracted (AVE) values ⩾ 0.50 (Hair et al., 2019).

3.7 Data Analysis Procedure

Data analysis was conducted in several stages:

1) Descriptive Statistical Analysis
   To summarize respondent characteristics and general trends of each variable.
2) Measurement Model Evaluation
   Using CFA to assess the adequacy of the measurement model.
3) Structural Model Testing
   To evaluate hypothesized relationships among latent variables.
4) Model Fit Assessment
   Model fit was evaluated using several goodness-of-fit indices, including Chi-square/df, RMSEA, CFI, TLI, and GFI. The model was considered acceptable if it met recommended cutoff values (Hair et al., 2019).
5) Hypothesis Testing
   Hypotheses were tested based on standardized path coefficients and significance levels ($p < 0.05$).

3.8 Ethical Considerations

Ethical principles were strictly observed throughout the research process. Participation was voluntary, informed consent was obtained from all respondents, and anonymity was maintained. The data collected were used solely for academic research purposes.

4. RESULT AND DISCUSSION

4.1 Results of Testing with SPSS Version 22

This reliability test was used to see the extent to which the measurement results were relatively consistent. It was considered reliable if the Cronbach alpha value was greater than 0.5. The reliability test was conducted using IBM SPSS version 30, and the results are as follows:

Table 01. Reliability Statistics.

Cronbach's Alpha	Cronbach's AlphaBased on Standardized Items	NofItems
0.897	0.954	6

In Table 1, with 75 respondents and 172 statements, Cronbach's Alpha value is 0.897 and Cronbach's Alpha based on standardized items is 0.954, indicating perfect and very high reliability.

Table 02. Summary Model Correlation.

Mode I	R	R Square	Adjusted R Square	Std. Error of the Estimue	Change Statistics					Durbin Watson
					R Suare Change	F Change	df1	df2	Sig.f change	
1	,954	,875	,867	2,321	,875	47,727	5	34	,000	1,856

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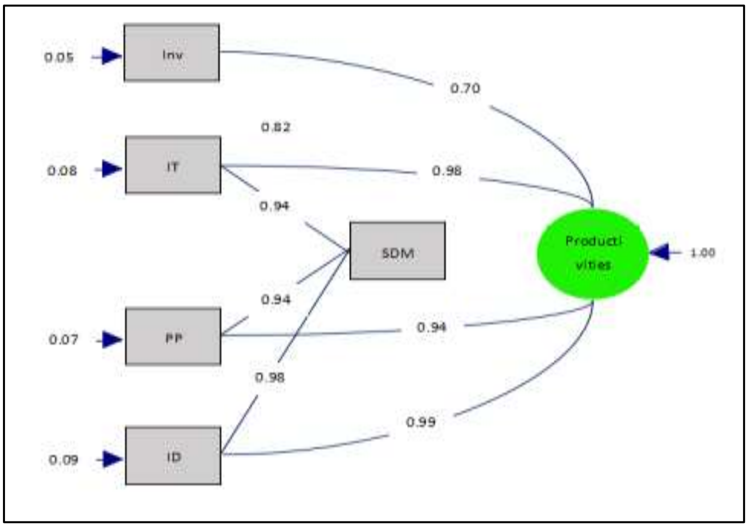
The table in the summary model explains the correlation or relationship (R) between the Predictor (Constant) or independent variable (X), namely Inventory (Inv), Information Technology (IT), Training and Development (PP), Data Integration (Id), and Competent Resources (Sdm) with a Productivity determination coefficient of R = 0.954 a and an R-squared of 0.875, which indicates that the influence of independent variables on dependent variables is 0.875 or 87.5%, and an adjusted R-squared of 0.867.

4.2 Test Results with SEM (Structural Equation Modeling).

Model Testing using SEM

In this test, the measurement model was obtained from the results of the Full Standard Solution measurement presented in the following figure:



Goodness of Fit Statistics

Degrees of Freedom = 5

Minimum Fit Function Chi-Square = 30.235 (P = 0.027)

Normal Theory Weighted Least Squares Chi-Square = 30.235 (P = 0.055)

Estimated Non-centrality Parameter (NCP) = 12,80

90 Percent Confidence Interval for NCP = (12.80 ; 30.43)

Minimum Fit Function Value = 0.32

Population Discrepancy Function Value (F0) = 0.15

90 Percent Confidence Interval for F0 = (0.0 ; 0.50)

Root Mean Square Error of Approximation (RMSEA) = 0.073

90 Percent Confidence Interval for RMSEA = (0.050 ; 0.080)

P-Value for Test of Fit (RMSEA > 0.05) = 0.05454

Expected Cross-Validation Index (ECVI) = 0.74

90 Percent Confidence Interval for ECVI = (0.64 ; 1.14)

ECVI for Saturated Model = 0.76 ,ECVI for Independence Model = 9.08

Chi-Square for Independence Model with 10 Degrees of Freedom = 344.11

Independence AIC = 354.11, Model AIC = 28.20, Saturated AIC = 31.42

Independence CAIC = 367.56, Model CAIC = 60.24, Saturated CAIC = 64.90

Normed Fit Index (NFI) = 0.96, Non-Normed Fit Index (NNFI) = 0.93

Parsimony Normed Fit Index (PNFI) = 0.70

Comparative Fit Index (CFI) = 0.95, Incremental Fit Index (IFI) = 0.95

Relative Fit Index (RFI) = 0.97, Critical N (CN) = 150.56

Root Mean Square Residual (RMR) = 0.022

Standardized RMR = 0.012, Goodness of Fit Index (GFI) = 0.85

Adjusted Goodness of Fit Index (AGFI) = 0.82

Parsimony Goodness of Fit Index (PGFI) = 0.94

4. CONCLUSION

This study examined the determinants of construction productivity in West Sumatra by integrating inventory management, information technology utilization, employee training and development, analytical data integration, and human resource competence within a Structural Equation Modeling (SEM) framework. The findings demonstrate that construction productivity is influenced by a combination of managerial, technological, and human resource factors that interact dynamically within project environments. The results of the SEM analysis indicate that inventory management, information technology utilization, employee training and development, and analytical data integration have significant positive effects on human resource competence and construction productivity. Human resource competence emerges as a critical mediating variable that strengthens the impact of organizational systems and technological adoption on productivity outcomes. This finding confirms that productivity improvement cannot be achieved solely through technological investment or managerial reform without corresponding improvements in workforce capability.

Furthermore, the study highlights the importance of data-driven decision-making in construction management. The integration of analytical data enables better monitoring of project performance, more accurate resource allocation, and proactive problem-solving, which collectively enhance productivity. Effective inventory management supported by information technology reduces material-related delays and operational inefficiencies, contributing to smoother project execution. From a theoretical perspective, this research contributes to the construction management literature by providing an integrated empirical model that captures the complex interrelationships among productivity determinants. The application of SEM offers a more comprehensive understanding of both direct and indirect effects, addressing limitations of previous studies that examined productivity factors in isolation.

Practically, the findings suggest that construction companies should adopt an integrated productivity improvement strategy that combines effective inventory management systems, advanced information technology, continuous employee training, and data integration supported by competent human resources. Policymakers and industry stakeholders are encouraged to support workforce development programs and digital transformation initiatives to enhance productivity performance across the construction sector. Despite its contributions, this study has certain limitations. The research is geographically limited to West Sumatra, which may affect the generalizability of the findings to other regions. Future research is recommended to expand the study area, incorporate longitudinal data, and explore additional variables such as organizational culture and leadership style to further enrich the productivity improvement model.

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